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Towards Autonomous Agents for Precision Agriculture

[1]*Udenze Adrian, [2]Alumona Theophilus Leonard, [3]Isizoh Anthony Nosike

[1,2,3]Department of Computer and Electronics Engineering, Faculty of Engineering, Nnamdi Azikiwe University, Awka, Nigeria

***Abstract* - Wireless Sensor Networks are increasingly being applied in Precision Agriculture to minimize farming resources and maximize crop yield. Data on environmental and soil conditions can be collected by Sensor Nodes on a fine scale and transmitted to Base Stations where they are analyzed to aid decision making in a farm. Furthermore, using current Artificial Intelligence techniques, Agents that learn directly from the environment can be deployed such that the entire system, from data collection to analyses and decision making is completely autonomous. This research work presents results for the design and implementation of a low cost Wireless Sensor Network equipped to sense soil moisture, pH and NPK levels as well as environmental temperature and humidity levels. The sensed data is transmitted to a Base Station for online publishing and analyses using a Reinforcement Learning DQN Agent.**

Keywords: Autonomous Systems, Wireless Sensor Networks, Precision Agriculture, Deep Neural Networks, Reinforcement Learning, Deep Q Networks.

1. Introduction

Agriculture, as every other big business, is technology driven to increase yield and reduce resources. Getting more yield for less resources increases the farmer's profits and also increases the sustainability of farming. To manage resources better, plant, soil and environmental conditions are closely monitored so that scarce resources are judiciously utilized. This modern way of farming is termed Precision Agriculture (PA) [1,2,3].

WSNs have been proven to be able to collect environmental data in a cost effective way [4]. The soil conditions (moisture, light, temperature, pH, NPK) in a 1-acre farm will not be uniform, both in time and space [5]. In a large farm and over a long time period, the variations are likely to be even more pronounced. Yet until very recently, in critical decision making scenarios, the farm is assumed to be homogeneous, e.g. apply 1 kg of fertilizer per x meter, sprinkle x amount of water twice a day. Today, hand held electronic devices have given farmers the ability to take readings of soil conditions frequently and quickly to be able to make better informed decisions. Going a step further, WSNs have given farmers the ability to collect data over a large area in small time frames over a large period of time cost effectively [6,7]. With the large amounts of data have also come more advanced decision making engines based on AI Agents [8,9,10,11,12]. Just as it would be impossible to expect a farmer to collect soil data every minute over a large area for a year, so is it impossible to expect the farmer to analyze data coming in at a rate of 10s or even 100s per minute, depending on the network size. AI engines provide the mechanism to take advantage of the large amounts of data and make optimal decisions on how resources are used, so as to minimize costs while at the same time maximizing yield.

There are a range of WSN nodes in the market today as well as a broad range of sensors [13]. For PA to be viable, the cost of implementing a network must be lower than the gains made in increased yield and reduced cost. The design of a network is a decision making process to adjudicate competing requirements. For example, to provide longer radio links, more power is required, more power means more costs.

This paper presents the design and implementation of a WSN for PA. The network is designed to measure environmental conditions in a farm namely soil moisture, pH and NPK levels; as well as temperature and humidity; using low cost devices and also open source technologies. Using open source platforms enables us to access state of the art tools and technologies and also gives us a legal platform on which to develop and eventually license our own technologies. To this end, we have chosen an Arduino Uno [14] based system for the Sensing Nodes (SN) and a Raspberry Pi, [15], for the sink node or BS. We have used the well-established Zigbee [16] chip-set for radio communications.

AI agents also come in a range of complexity to suit different requirements. Whereas a simple Reflex Agent might be sufficient to control a washing machine, problems in nature require more sophisticated Agents [17]. A continuous time problem for example, implies an infinite state and or action space and can only be learned by approximating a continuous time function [18]. A state of the art DNN [19] is able to theoretically approximate any function given enough labeled samples. In an environment where samples or models do not exist, training of a conventional DNN cannot occur, time must be spent acquiring and sorting samples and models before learning can begin. A RL agent [18] on the other hand, learns by interacting with the environment. A RL agent is therefore able to learn autonomously from its environment by maximizing a reward signal. In this paper we also discuss our

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proposed framework for achieving a low cost autonomous system for PA.

The rest of the paper is organized as follows: A literature review is followed by a methodology section; results are then presented followed by conclusions. Acknowledgments and References finally presented.

2. Literature Review

A good overview of PA can be found in [3]. In chapter 1, the authors define PA as a technology that can be used to improve profitability while reducing the impact of agriculture on the environment. The authors in [26] go further by conducting a systematic review of state of the art technologies used in PA. These techniques include Global Position System (GPS) based PA, Remote Sensing (RS) based PA, On The Go Sensing (OTGS) and Yield Monitors (YM) based PA. GPS is predominantly used for identifying locations such that automated machines and or robots can be directed to precise locations. The work proposed in this research has a bearing on eventually adopting robots to carry out farming practices, however, it is not a primary area of concern. RS techniques are predominantly satellite based and not in the scope of the research proposed here. YM is primarily concerned with automated harvesting and yield measurement and although relevant to the extent that yield has to be evaluated as a measure of success or not of the techniques presented in this research, it is not a primary concern. OTGS is concerned with embedding sensors in farms to monitor field and soil conditions. This technology is the area of focus for this research.

In [6], the authors investigate the applicability of WSNs for PA and conclude that there is an incremental growth in the use of WSNs for monitoring agricultural fields, optimizing irrigation for crops, as well as measuring temperature and soil properties.

A good overview of WSNs can be found in [4]. Figure 1 below depicts a typical WSN where nodes equipped with radios send messages to neighbor nodes. Multi-hopped messages arrive at a BS which is equipped with more computing resources for data processing. Note that some applications may require sensed data to be stored and processed in the cloud [27].

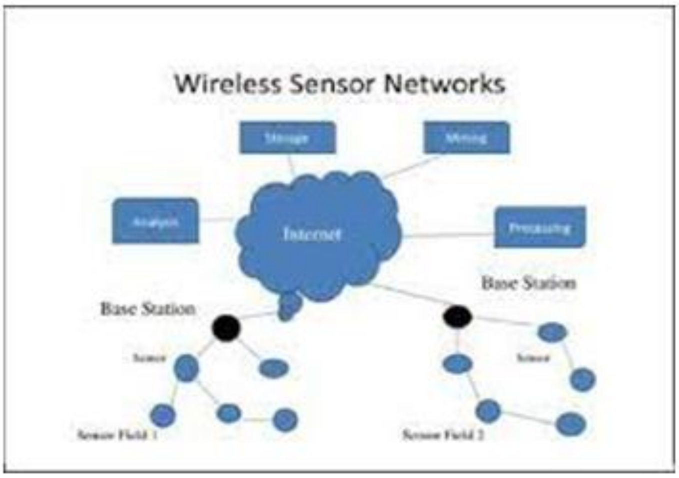

Figure 1: Typical Wireless Sensor Network

Off the shelf WSN nodes range in cost, from \$99 to \$750 for more powerful nodes (Sun spot), [13].

In [28], the authors propose a low cost WSN consisting of Arduino nodes. Arduino [14] is an open source platform for developing embedded devices and therefore a fraction of the cost of an off the shelf node, typically less than \$30.

Plants need nutrients, a soil with adequate moisture to convey the nutrients and sunlight for photosynthesis [29]. Soil moisture conditions significantly impact plant welfare and therefore it’s potential to grow. Some plants require a damp soil, others a dry soil [51]. To measure soil moisture, the authors propose to use an Arduino compatible soil hygrometer module [30]. Humidity and temperature have an influence on the rate at which water evaporates from the plant and soil, it may also affect the plant’s comfort, fruiting and flowering patterns [51]. Tomato fruits will not ripen at low temperatures for example [51]. To measure humidity and temperature, the authors propose to use the DHT22 module [31]. Light impacts plant’s well-being. Some plants prefer to grow in the shade, others like Peppers, like to have a lot of sunlight [48]. Sunlight also has an impact on the rate of moisture loss and can therefore be used to plan for water. An Arduino compatible light sensor module is the LDR Photosensitive module [52]. Soil acidity (pH) affects a plant’s ability to absorb nutrients. A chart of the effects of soil acidity on plant nutrients can be found in [29]. To measure soil pH, the authors propose to use an Arduino compatible pH sensor module [33]. Nitrogen, Phosphorous and Potassium are essential nutrients for plant growth and can be measured using a JXCTIOT NPK sensor module[32]. Finally, 2 nodes will be equipped with cameras to monitor pests, weed and the environment. The Adafruit TTL weatherproof camera is proposed for this research [53].

A Raspberry Pi [15] Arduino combination WSN is proposed in [34]. Raspberry Pi is a credit card sized computer

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with enough resources to run an OS, Applications and a high level programming language like Python. Python [35] has extensive libraries [19,36] for AI [17] and Data Mining [37]. To connect to the internet, a GSM module [39] will be connected to the Raspberry Pi. AI has been applied in agriculture to a wide range of problems, Computer Vision to monitor grain crops [38], crop yield prediction and nitrogen status estimation [11], optimization of irrigation and application of herbicides and pesticides [40]. Comprehensive reviews of AI in agriculture can be found in [8,41,42]. Neural Networks [43] in particular play a big part in AI due to its ability to approximate theoretically any function. DNN [19] dominate in regression and classification tasks such as computer vision, yield estimation and large decision making problems. The draw back with conventional DNN is that large labeled sample sets are required to train the network before optimal behavior is achieved.

RL [18] is an AI technique that does not require samples nor models of the environment to learn optimal behavior. By interacting directly with the environment, a RL agent learns optimal rational behavior. Applications of RL to a number of problems can be found in [37,44,45]. Furthermore, for problems with large state and action spaces, such as continuous time problems, RL can be combined with the function approximation qualities of DNN (called a DQN) so that DQN training takes the form of direct interactions with the environment, removing the need for training samples. AI has been combined with WSN and applied in PA, [46,47]. The aim of the proposed research is to apply PA to crops typically grown in Nigeria. Farming practices associated with growing the chosen crops can be found in [48, 49, 51]. Ideal growing conditions for these crops are summarized in the table below.

Table 1: Ideal growing conditions for chosen crops

Crop	**Temperature**	***Soil moisture***	***Light***	**Humidity**	pH	N-P-K mg/kg	References
Tomatoes (Solanumlycopersicum)	19 – 30 F in the daytime. Nighttime below 85 F to ripen.	Damp soil – to be calibrated with the meter.	8 hrs or more sunlight. Low intensity.	*65-70%*	*5.5-7.5*	20-50-175	*[50,51]*
Pepper (Capsicum annuum L)	19 – 26 C daytime.	Well drained	8 hrs or more sunlight. Low intensity.	65-80%	6-6.8	20-50-175	[48]
Ugu (Telfairia Occidentalis)	21 – 30 C	Well drained	8 hrs or more sunlight.	*70 – 80%*	*4.5 - 6*	*20-50-175*	*[49]*

3. Methodology

Our design goals for the WSN can be summarized as follows:

1) The WSN should be able to collect soil and environmental data from a farm.
2) The WSN should be able to make the data collected available in any part of the globe with the aid of IoT.
3) The data collected can also be stored locally using a local database to aid Machine Learning.
4) The WSN should support the implementation of Agents to aid autonomous decision making.
5) The WSN must be low cost.

Our solution was to implement WSN SNs based on Arduino Uno boards. Such a node is low cost, extensible and re-configurable, it is also open source with strong user communities and excellent documentation. One SN was equipped with Temperature, Humidity, Soil Moisture and Soil pH sensors, the other was equipped with an NPK sensor; both SNs were equipped with Zigbee radio modules for communication with the BS.

To support Machine Learning and implementation of autonomous decision making, we used a Raspberry Pi for a BS. The BS was equipped with a GSM module for internet communications and a Zigbee module configured to be a Router.

Figure 2 shows block diagrams for the WSN BS and sensor nodes, using off the shelf hardware components. Figure 3 shows high level flow charts for system software.

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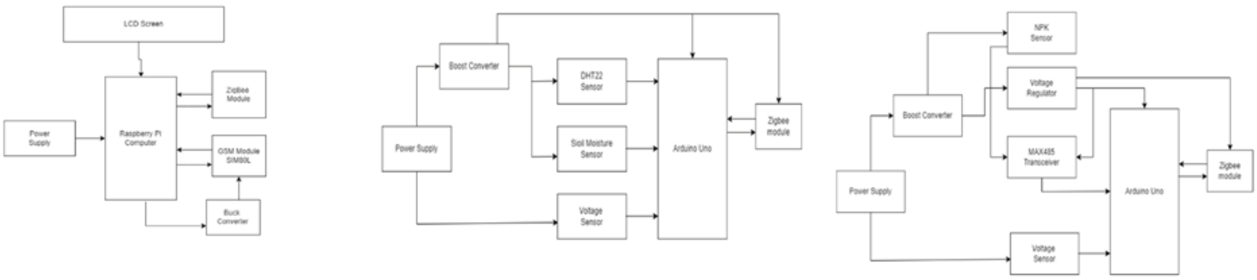

Figure 2: Block diagrams for the WSN BS and SN

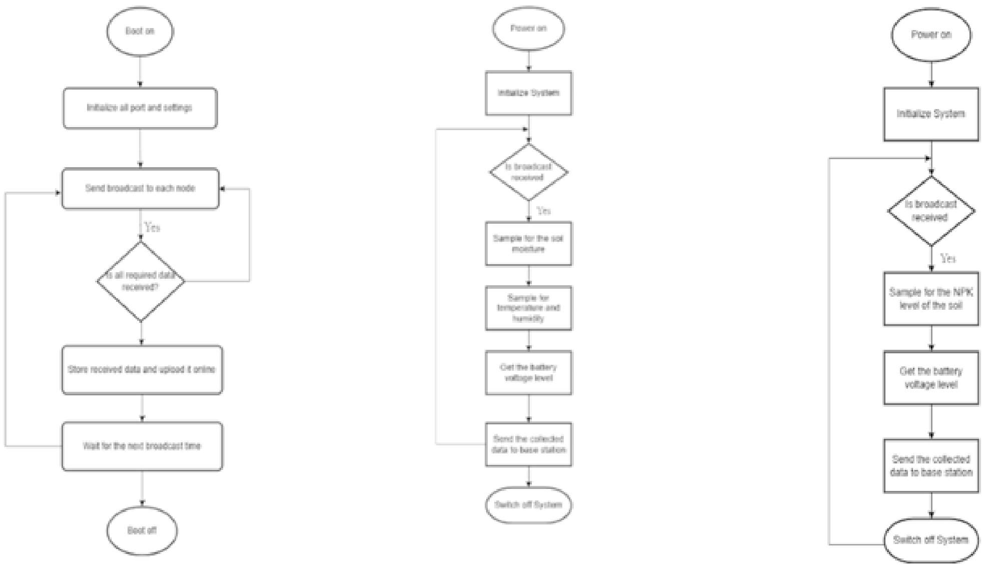

Figure 3: low chart diagrams for system software

The WSN described above is able to sample data and transmit to a BS every minute or even a number of times a minute. For a network of 20 sensors this equals 1200 samples per hour; over the course of a week the number of data samples top 100,000. To effectively analyze this quantity of data we designed and implemented a RL Agent. The agent interacts with the environment by getting sensor readings at predetermined time intervals. Based on the received sensor reading (Percepts), the RL agent has a picture of the environment and is said to be in state *s* at time t (s_t). The agent then responds to the Percept by deciding on a best choice of action *a* from a set of actions *A* based on a policy π. The policy π is based on a state Value Function (VF), $Q^{\pi}(s,a)$. The optimal Q function, $Q^{o}(s,a)$ is defined as the maximum rewards that can be accrued starting from state *s*, taking action *a* and following the optimal policy. The optimal Q-function obeys the Bellman optimality equation [18]:

$$Q^{o}(s,a) = E[r + \gamma max_{a'} Q^{o}(s',a')] \qquad (1)$$

Where s', a' are next states and actions respectively and γ is a discount value.

By using the Bellman equation as an iterative update,

$$Q_{i+1}(s,a) \leftarrow E[r + \gamma max_{a'} Q_i(s',a')] \qquad (2)$$

It can be proved that the above update rule converges on the optimal Q-function as *i* goes to infinity, [18]. The action taken by the agent brings about a change in the environment and at the next point in time, t+1, the agent finds itself in another state s_{t+1} based on the Percept received from the environment. The agent also receives a scalar reward (r_{t+1}) which is used to update it's VF. By combining a DNN with RL we end up with an Agent that learns a set of parameters, weights of a neural network, by interacting with the environment.

Thus a neural network with parameters θ is trained to approximate the Q-values i.e.

$$Q(s,a;\theta) \approx Q^{o}(s,a)$$

By minimizing the following loss at each step *i*:

$$L_i(\theta_i) = E_{s,a,r,s' \sim \rho(.)}[(y_i - Q(s,a;\theta_i)^2)] \qquad (3)$$

$$\text{Where } y_i = r + \gamma max_{a'} Q(s',a';\theta_{i-1})$$

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y_i is the Temporal Difference (TD) target and y_i-Q is the TD error; ρ represents the behavior distribution over transitions *s,a,r,s'* collected from the environment.

This type of Agent is termed a Deep Q Network [19], and is able to converge on near optimal results for problems with a large State space and Discrete and finite Action space.

We formulated our problem as a continuous discounted task in which the Goal is to keep the soil and environmental conditions within a predefined range of values or states. For every time step, the Agent receives a Reward of +10 if the sensor readings are within the predefined states. Actions in each non Goal state are: apply 1 of 4 units of Fertilizer, reward of -1 per unit; apply 1 of 4 units of water, reward of -1 per unit; or apply 1 unit of both, reward of -2. As a result of an Action, the State of the Environment changes following a MDP.

The above described WSN was deployed in a sample pepper farm measuring 5sqm. Another farm was also set up without PA for comparison of yield and resources. Data was collected by SNs over the crop life cycle and transmitted to a BS equipped with our DQN RL agent. Ideal conditions for growing pepper is given in table 1 above. The Agent state space is confined to a set number of states. Each sensor reading was quantized to be in one of four values; each sensor value was normalized to a value between 0 and 1.

4. Results

The WSN was built and tested for core functionality namely, reading accurate soil and environmental conditions from each node, transmitting data to BS, publishing the data on the internet and implementing a RL Agent.

Figure 4 below shows WSN node builds for BS, SNs, as well as test results for the Zigbee module configurations and data transmission. Starting from bottom left of the figure, builds for the Raspberry Pi and Arduino modules (bottom middle) can be seen. Bottom right picture shows SN configuration settings, top right, middle and left show successful transmission results between SN and BS.

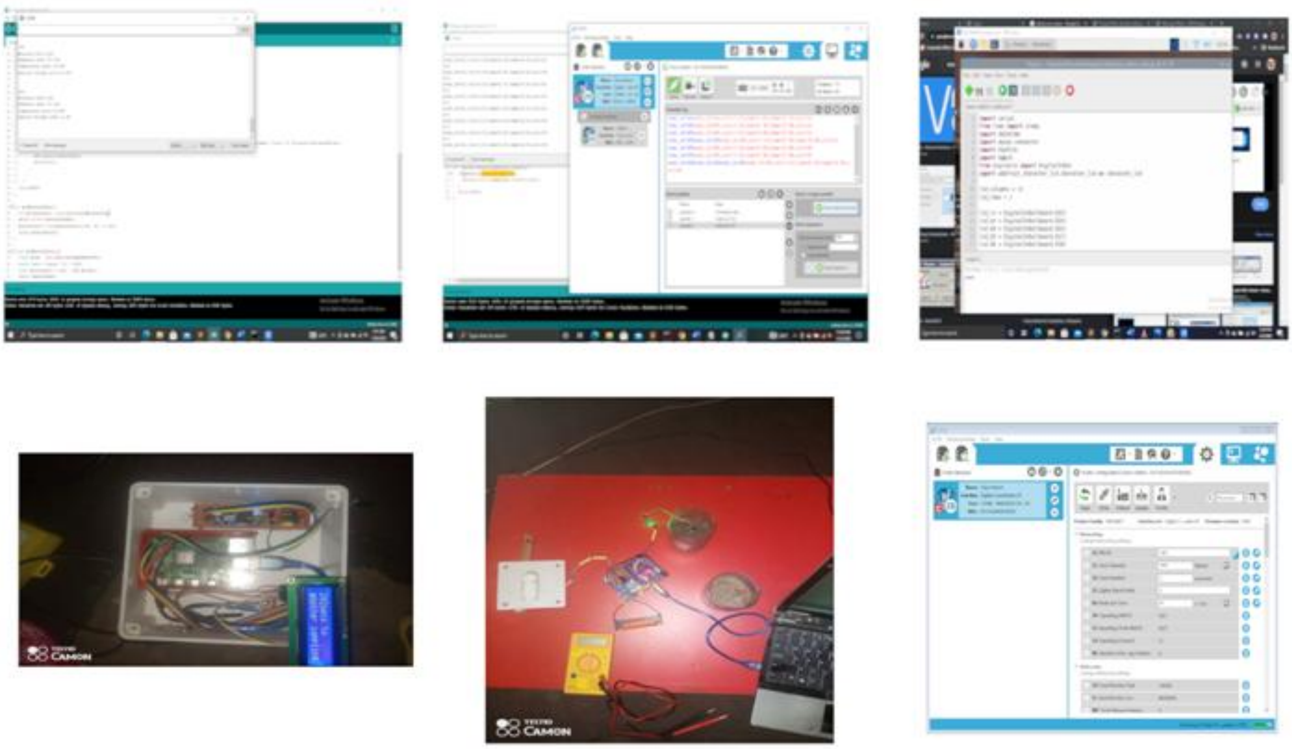

Figure 4: Bottom left and middle: build of BS and SN; bottom right, top right and middle: configuration of SNs; and top left: successful transmission of data from SN to BS

Figure 5 below shows results for the RL Agent. It can be seen that the optimal long term reward signal was achieved after approximately 1000 iterations. With the SNs programmed to sense and send data to the BS every half hour, this translates to the agent performing near optimally after about 20 days. Table 2 shows the resources used to grow the pepper crops for both the PA farm and non-PA farm. It can be observed that 73% and 80% savings were made for water and fertilizer respectively while yield levels remained equivalent for both farms.

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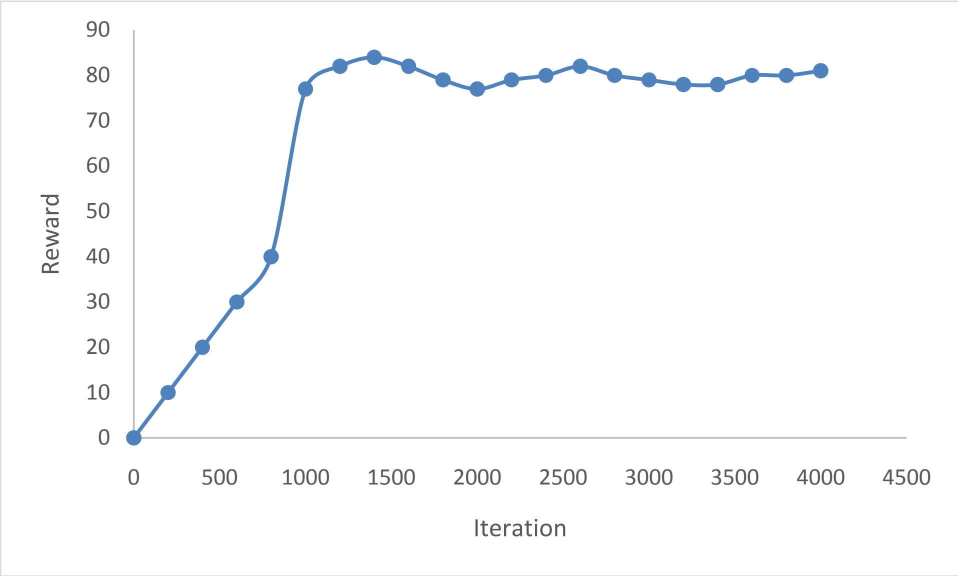

Figure 5: Performance of DQN agent showing number of iterations before reaching optimality

Table 2: Resources used in PA farm Vs non-PA farm

Resource	PA farm	Non-PA farm	Savings
Water (Liters)	330	1250	73%
Fertilizer (Kg)	1kg	5kg	80%
Yield (Kg)	1.9	1.89	

5. Conclusions

We have presented a low cost WSN for collecting data in a farm. We have also presented a RL Agent for analyzing collected data so that autonomous decision making can happen. Our autonomous PA system was successfully built using low cost off the shelf components and deployed on a small farm of peppers. For comparison, a similar farm was setup without PA. Our results show that the WSN system was able to sense and transmit data to a BS equipped with a RL Agent. The Agent reached optimality after approximately 1000 data points and over the lifecycle of the crop, a 73% reduction in water and 80% reduction in fertilizer was achieved without impacting the crop yield when compared to a farm without PA. Our research clearly shows the benefits of WSN and DQN based PA and we will be scaling up the work done in this research in future.

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